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# A new approach for detecting abnormalities in mammograms using a computer-aided windowing system based on Otsu's method

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**Abstract**

Breast cancer is the most common cancer and the leading cause of cancer deaths in women worldwide. This study aimed to provide an automatic windowing method in mammograms, based on the principles of Otsu's thresholding function, to help radiologists more easily detect abnormalities on mammograms. A total of 322 mammographic images from the Mammographic Image Analysis Society (MIAS) database were used in the present study. The image background was removed based on Otsu's method. After selecting the threshold in the computer-aided windowing (CAW) system, the pixel values were kept larger than the threshold and displayed on a grayscale. A radiologist evaluated images randomly before and after CAW. Using CAW, the radiologist correctly diagnosed all healthy images (207 images). A total of 115 mammograms were evaluated to differentiate malignancy from benign masses. All 63 benign images were accurately diagnosed after using CAW. Moreover, of 52 malignant images, all were accurately recognized as malignant except one, which was recognized as benign. Therefore, specificity and sensitivity were significantly improved to 98% and 99.6%, respectively, and the area under the receiver operating characteristic (ROC) curve was calculated to be 0.99. The study showed that the use of CAW can potentially lead to quicker image assessment and improve the diagnostic accuracy of radiologists in differentiating between benign and malignant masses on mammograms.

**Keywords** Computer-aided diagnosis · Breast cancer · ROC curve · Computer-aided windowing · Thresholding

## 1 Introduction

Breast cancer is the most common form of cancer and the leading cause of cancer deaths in women worldwide; it has a higher occurrence in women from less developed countries than those from more developed countries [1]. Screening mammography can reduce mortality by more than 40%, compared with the mortality in unscreened women [2]. The American Cancer Society recommends that women between the ages of 40 and 44 years should have their first annual breast cancer screening conducted by a physician, accompanied by a mammogram [3].

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The detection of benign and malignant lesions is difficult because of the variable shapes and sizes of breasts and non-recognition of lesions in the breast parenchymal tissue. According to available evidence, 10–30% of breast lesions discovered during routine screening are misdiagnosed by radiologists [4]. Therefore, better detection of breast malignancy can effectively reduce unnecessary biopsies. A variety of mathematical methods have been suggested for automatically detecting microcalcifications on mammogram images using a computer-aided diagnosis (CAD) system, for example, Otsu's method [5, 6] and wavelet transform [7, 8]. It has been shown that the use of CAD systems increases the number of true positives detected (cancer is diagnosed correctly) while decreasing false negatives missed (cancer is ignored incorrectly) [9, 10]. However, importantly, the diagnosis of breast cancer is not done using CAD systems. Because of the importance of early detection of cancer, radiologists prefer mammography as the final diagnosis and decisions are made by a radiologist on the basis of the mammogram. The radiologist must detect and confirm cancer or microcalcifications by changing the contrast of the images by manually adjusting the window level. CAD systems help the radiologist in diagnosing cancer by emphasizing the possibility of cancer [11, 12]. In other words, radiologists usually try to improve detection efficiency by changing the image contrast. However, this procedure is relatively time-consuming because differences in breast mass (size and composition of glands and fat) affect the appearance of a portion of the chest on the mammography image. Lack of time, crowded wards, and fatigue negatively affect the selection of the appropriate window and may increase false negatives and false positives [13, 14].

This study presents a computer-aided windowing (CAW) system in mammograms based on principles of Otsu's thresholding, which change the contrast of the mammographic image automatically; therefore, it can be a good starting point for mammogram evaluation by radiologists to detect abnormalities in a quicker and easier manner.

## 2 Materials and methods

### 2.1 Mammographic images

A total of 322 mammographic images from the Mammographic Image Analysis Society (MIAS) database of the University of Essex, England, were used in this research [15]. In addition to having diverse mammographic images, the MIAS database displays breast tissue characteristics and some information about abnormalities (calcification, circumscribed masses, ill-defined masses, spiculated masses, architectural distortion, and asymmetry) and severity of the disease (benign and malignant) based upon biopsy. The size of all the images was $1024 \times 1024$ pixels at 200 μm resolution.

### 2.2 Computer-aided windowing (CAW)

When evaluating the images of histograms of the MIAS database, it was observed that the histogram of mammographic images had a double peak and pixel values were separated into two classes with different variances and mean level (Fig. 1). Usually, microcalcification and malignant tumors are more absorbent and are placed in a second class with larger pixel values and a higher mean level.

Therefore, the manipulation of subjects' appearance occurs in trying to remove the first-class values because the background has no diagnostic value. A suitable tool to remove the background from the object is thresholding based on Otsu's method. This method is used in various techniques in the medical field [16–18], especially in the automatic segmentation of masses in digital mammograms [5]. After selecting the threshold in our CAW method, the pixel values are kept larger than the threshold and displayed on a grayscale and values smaller than the threshold are converted to zero (black). In fact, the low level of the window is the same threshold and windowing is reduced on the pixel values of the second class.

The threshold selecting based on Otsu's method was used to obtain a suitable low-level window (LLW) to remove the background. However, this method is sensitive to the distribution of image values in pixels. This means that the threshold will be shifted to the class with a greater number of pixels [19].

In most of the images that were evaluated, most pixel values belonged to the first class and the thresholds were similar to lower values; therefore, LLWs were not appropriate. To solve this problem, LLW was increased

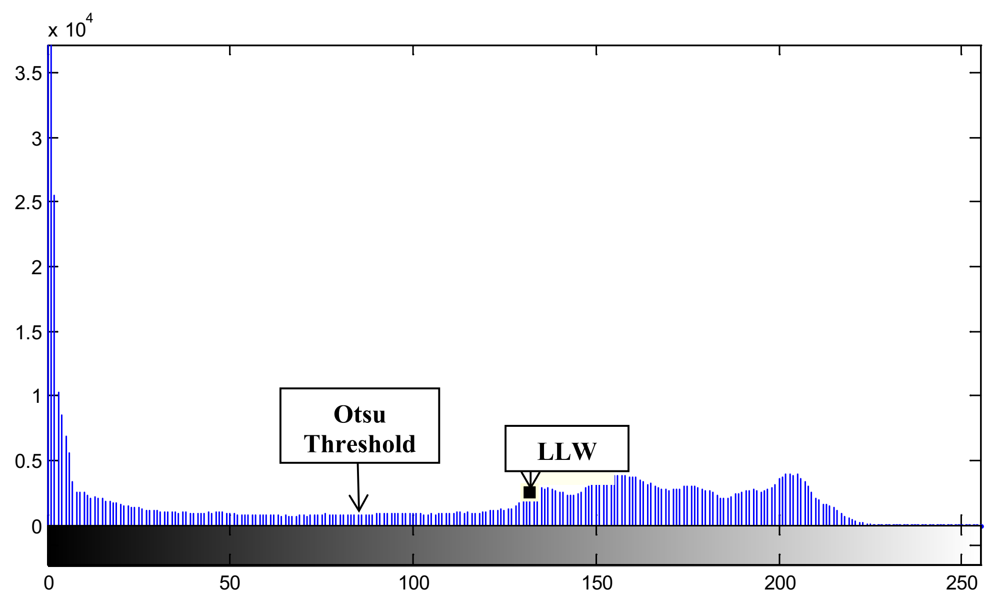


**Fig. 1** Histogram of the MIAS database images in which the threshold based on Otsu's method is 88, whereas the LLW, based on Eq. 1, is 132. *LLW* low-level window, *MIAS* Mammographic Image Analysis Society

according to the standard deviation (SD) of the images' pixel values within the second class. Reviewing the histogram of mammographic images and its threshold based on Otsu's method, it was observed that subtracting a fraction of the SD of second-class values from the mean of second-class values (Eq. 1) led to a convenient LLW, and in this state, an image with acceptable quality was achieved (Fig. 2).

$$\text{LLW} = \text{Mean} - F \times \text{SD}, \tag{1}$$

here $F$ is an empirical number selected in this study, with "1″ based on an experienced radiologist's assessment of a different window. For example, the threshold based on the method was 88 for Fig. 1. On the other hand, the SD and the mean values of the image's second class were 32 and 164, respectively. Consequently, instead of distributing 256 colors between 88 and 255 on a grayscale, colors between 132 and 255 were distributed. By applying Eq. 1, the window was narrowed to 44 units compared with the direct use of the Otsu threshold, as shown in Fig. 1.

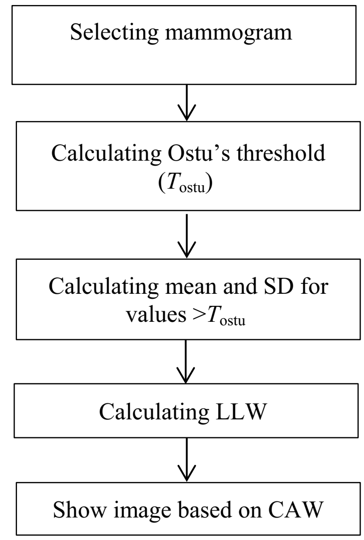


**Fig. 3** Flow diagram of filtration and evaluation of mammograms. *SD* standard deviation, *LLW* low-level window, *CAW* computer-aided windowing

## 2.3 Evaluation of CAW

A radiologist with less experience reviewed the 322 MIAS database images on an HP Pavilion notebook with a 15.6-inch liquid crystal display (LCD) monitor with a resolution of 1366 × 768 pixels. Each image was assigned one of the following scores: (1) definitely no cancer, (2) probably no cancer, (3) possibly cancer, (4) probably cancer, and (5) definitely cancer. Each of the 322 images after CAW was reviewed randomly again based on a flow diagram (Fig. 3). First, after selecting mammograms randomly, the threshold was calculated based on the Otsu method. Second, SD and mean of the pixel value larger than that of the calculated threshold were calculated and then the LLW of each image was calculated using Eq. 1. Finally, filtered images were saved for evaluation by the radiologist. During evaluation of all images with and without CAW, the radiologist could not change image contrast and could not apply any filter, mask, or convolution matrix. The interpretation environment was the same for all images, both filtered and unfiltered. These functions were accomplished using MATLAB software (MathWorks, Natick, MA, USA).

## 2.4 Statistical analysis

Receiver operating characteristic (ROC) curves were plotted using SPSS 18.0 (SPSS Inc., Chicago, IL, USA) for all original and filtered images. The area under the curve was calculated for the states with and without filters and the images compared by paired $t$ test with each other. A $p$ value threshold of 0.05 was considered to be significant.

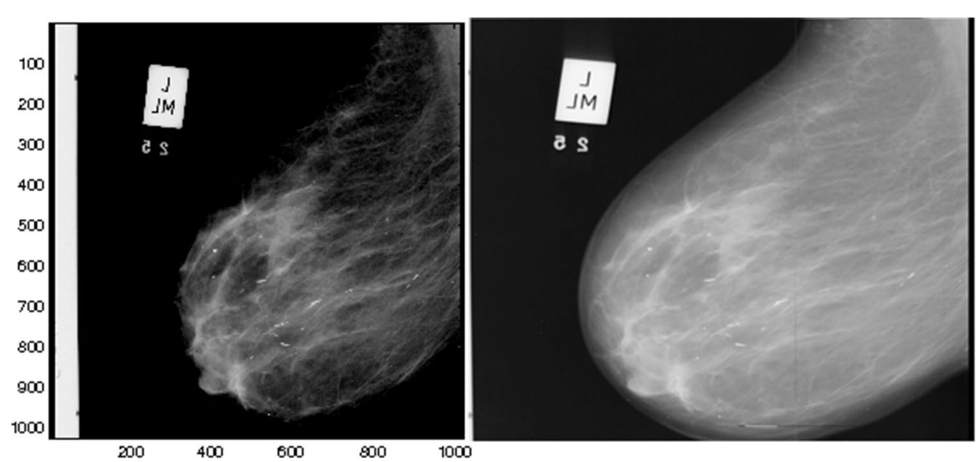


**Fig. 2** One of the MIAS database images before (right) and after (left) changing contrast base using CAW. *MIAS* Mammographic Image Analysis Society, *CAW* computer-aided windowing

**Table 1** Results of 322 mammograms evaluated for detection of abnormalities

| | Definitely not present | Probably not present | Possibly present | Probably present | Definitely present | Total |
|---|---|---|---|---|---|---|
| No cancer | 45 | 207 | 11 | 7 | 0 | 270 |
| Cancer | 0 | 35 | 10 | 7 | 0 | 52 |
| Total | 45 | 242 | 21 | 14 | 0 | 322 |

**Table 2** Sensitivity, specificity, and false-positive rate (FPR) for detection of abnormalities

| | Sensitivity | Specificity | FPR |
|---|---|---|---|
| Probably not present | 1 | 0.2 | 0.8 |
| Possibly present | 0.3 | 0.9 | 0.1 |
| Probably present | 0.1 | 1 | 0 |
| Definitely present | 0 | 1 | 0 |

FPR = 1 – specificity

The results are expressed in terms of sensitivity or "true positive" (TP) and specificity or "true negative" (TN). Sensitivity is the probability that a person with the disease has been correctly diagnosed. Specificity is the probability that a healthy person has been correctly diagnosed as healthy.

It should be noted that the use of the ROC curve for the evaluation of radiographic images, especially mammographic images, has recently become very popular to compare different devices or techniques [20–22].

## 3 Results

A total of 322 mammographic images from the MIAS database were evaluated by a radiologist. It was found that there were 207 normal images, 63 images with benign, and 52 images with malignant. In the first section of evaluation, images containing benign were determined to be "probably no cancer." After the evaluation of the unfiltered images without CAW, 155 of 207 normal images were identified and it was reported that malignancy was "probably not present." For the rest of the images, it was reported that malignancy was "probably present" (greater certainty), that is, containing the disease (Table 1). At this stage, no image was conclusively diagnosed as malignancy "definitely present" and certainly no malignant image was reported as "definitely not present". Based on the results in Table 1, sensitivity and specificity were obtained, as shown in Table 2.

After using CAW, all healthy images (207 images) were correctly detected (Table 3) and sensitivity and specificity were observed to be very good (Table 4). Only one image that depicted a malignant was reported as benign but all other images with benign or malignant were correctly diagnosed.

A total of 115 mammograms were evaluated for differentiating between malignant and benign. In differentiating benign abnormalities from malignancies, the results based on the image without using CAW are troubling. Without using CAW, the area under the ROC (AUROC) curve was found to be 0.522 using SPSS software, indicating no significant difference compared with the area under the diagonal line ($p = 0.690$). After using CAW, all malignancies were accurately diagnosed except for one case (Table 5). The AUC was 0.990 and this difference was statistically significant compared with the area under the diagonal line ($p = 0.000$).

In the diagnosis of malignant from benign, sensitivity and specificity were observed to be 0.98 and 0.100, respectively, after using CAW.

**Table 4** Sensitivity, specificity, and false-positive rate (FPR) for detection of abnormalities after using computer-aided windowing (CAW)

| | Sensitivity | Specificity | FPR |
|---|---|---|---|
| Probably not present | 1 | 0.8 | 0.2 |
| Possibly present | 1 | 1 | 0 |
| Probably present | 1 | 1 | 0 |
| Definitely present | 1 | 1 | 0 |

**Table 3** Results of 322 mammograms evaluated for detection of abnormalities after using computer-aided windowing (CAW)

| | Definitely not present | Probably not present | Possibly present | Probably present | Definitely present | Total |
|---|---|---|---|---|---|---|
| No cancer | 207 | 63 | 0 | 0 | 0 | 270 |
| Cancer | 0 | 1 | 0 | 0 | 51 | 52 |
| Total | 207 | 64 | 0 | 0 | 51 | 322 |

**Table 5** Results of 115 mammograms evaluated for malignant vs. benign detection

| | Definitely benign | Probably benign | Probably malignant | Definitely malignant | Total |
|---|---|---|---|---|---|
| Benign | 45/**63** | 11/**0** | 7/**0** | 0/**0** | 63/63 |
| Malignant | 35/**1** | 10/**0** | 7/**0** | 0/**51** | 52/52 |
| Total | 80/**64** | 21/**0** | 14/**0** | 0/**51** | 115/115 |

No filter/**with filter**

## 4 Discussion

All images of the MIAS database were evaluated in two stages by a radiologist: before and after applying CAW. CAW was conducted in such a way that it illustrated higher values in images, which is compatible with past research suggesting the use of high-pass filters to delete the values of the image background and keeping the higher values [23]. As shown in Tables 1, 2, 3 and 4, some unexpected results were obtained. The radiologist recognized 100% of healthy cases after using CAW; 98% specificity and 99.6% sensitivity signaled significant improvement compared with 93% specificity and 33% sensitivity for the case when CAW was not used (Tables 1 and 2). A large body of research could optimize the accurate diagnosis of tumors and microcalcifications on the MIAS database based on different CAD methods [24–26]. According to the results, in most cases, the sensitivity and specificity were lower compared with the values shown in Table 4. For example, Sahba et al. [27] enhanced the diagnosis using the wavelet transformation of tissue suspected of cancer and utilizing weighting algorithms. After applying the filter to the MIAS database images, 81% sensitivity and 84% specificity were obtained. Mini et al. [28] exercised two types of wavelet transformation to detect microcalcifications automatically. Both concluded that wavelet transformation can reveal calcifications with 95% sensitivity in the MIAS database.

As shown in Table 5, among 115 malignant and benign images, all 63 benign images were accurately diagnosed after using CAW; moreover, among 52 malignant images, all were accurately recognized as malignant except one that was recognized as benign. The AUC for sensitivity against the 1-specificity curve was calculated to be 0.99, which was significantly different from the diagonal line ($p = 0.000$). Past studies that implemented the CAD method in mammographic images, reported AUC values between 0.8 and 0.96 [29, 30]. The AUC values using CAW may compete with those obtained using the CAD method. Tehrani et al. [31] showed the segmentation of suspiciously clustered microcalcifications by employing the fuzzy logic on wavelet coefficients on mammograms and image-processing algorithms for CAD, through which an AUC of 0.87 was achieved after separation. Niroui et al. [32] attempted to diagnose mammary lesions suspected of malignancy by employing the genetic algorithm and nervous network on the images of the MIAS database. Based on the results, the value of AUC increased from 0.73 to 0.84 by integrating these two mathematical techniques into one method, which can help radiologists more accurately render the clinical diagnosis of abnormalities.

Given the pathology and mammography results, mammography can play a pivotal role as a convenient and cost-effective method to detect breast cancer [33]. The use of computers and modifying contrast are highly recommended to increase efficiency in mammography results for the purpose of revealing microcalcifications and abnormalities in the breast [11, 34]. Azavedo et al. [12] discussed whether the accuracy of one radiologist's assessment of a mammographic image, with and without computer assistance, is the same as that of another radiologist. For this purpose, they reviewed 996 abstracts and 53 complete papers. The results indicated that minimum accuracy was equal to separate review by two radiologists when one radiologist assessed mammographic images by CAD. As shown in Tables 3 and 5, utilizing computers and optimizing contrast can reveal malignancy. The evidence in our study supports this, as our radiologist accurately diagnosed all malignancies except for one case. In other words, the results identify microcalcifications and assessment of abnormalities.

Jung et al. [6] reported that CAD can reduce the average assessment time of mammographic images without decreasing the radiologist's efficiency. During our study, the radiologist recognized malignant cases more efficiently with less reading time and was satisfied with the CAW.

False negatives (FNs) occur 10–25% of the time among healthy people and are regarded as one of the greatest obstacles in effectively detecting breast cancer through screening mammography. Monitoring a large number of images to find few cancer cases, compounded by difficulties with breast composition, fatigue, and the radiologist's own distractions, are regarded as some of the reasons for FN diagnoses [13, 14]. The implementation of automatic windowing reduced FN diagnosis (Table 3), coinciding with studies that have proven that employing CAD could reduce the FN rate in breast cancer diagnosis [35, 36].

Birdwell et al. [37] evaluated the mammograms of 8600 patients during a 19-month period. One of the seven radiologists who were invited to participate in the survey examined each mammographic image and reassessed the same image using CAD. The detection accuracy of those cancers, which had not been already recognized, increased by about 7.4%. In the present study, the definitive diagnosis of malignant cancers increased significantly after implementing automatic windowing, a finding congruent with those studies that employed CAD efficiently [36]. Despite the above-mentioned results, it is worth noting that inappropriate software or applications may reduce sensitivity or specificity, downgrading diagnostic quality [38].

Moayedi et al. [39] attempted to introduce a novel fuzzy classifier for mammographic images based on contourlet transform in breast cancer detection. Their experiments at best showed 95.6% classification accuracy on the MIAS database. In most CAD methods, the entire image turns into a balanced code (black and white), in which the microcalcifications are illustrated as white dots on a black background without showing breast tissue and composition. The radiologist, not the system, plays the main role in cancer diagnosis. Therefore, with a transform, breast tissue should be better visualized for accurate visual examination. Perhaps this will be one of the next methods to be adopted by radiologists to modify the contrast of mammographic images automatically, to quickly examine breast tissue and distinguish abnormalities in mammographic images. In the present study, the proposed method can be employed in medical image processing based on modifying the image windowing, in which the value of $F$ in Eq. 1 should be empirically decided based on diagnostic purpose to settle a suitable threshold.

## 5 Conclusion

In addition to enhancing sensitivity and specificity, the automatic windowing method results in a shorter monitoring time and in stronger image assessment, by which radiologists can more accurately diagnose as malignant or benign on mammograms. In other words, it seems that the image suggested by the automatic windowing method can be a good starting point for mammogram evaluation. Further studies are required to select the appropriate automatic window and to determine effects on sensitivity and specificity. In addition, quantitative studies should be conducted, especially with respect to the average time for accurate diagnosis by radiologists. To conclude, radiologists should utilize the automatic windowing method, because it improves mammogram viewing beyond manual contrast, is quicker to use in cancer diagnosis, and lends itself to a more accurate diagnosis.

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## Compliance with ethical standards

**Conflict of interest** The authors declare that they have no conflict of interest.

**Ethical approval** This article does not contain any studies with human participants or animals performed by any of the authors. This article does not contain patient data.

## References

1. Torre LA, Bray F, Siegel RL, Ferlay J, Lortet-Tieulent J, Jemal A. Global cancer statistics, 2012. CA Cancer J Clin. 2015;65:87–108.
2. Morrell S, Taylor R, Roder D, Robson B, Gregory M, Craig K. Mammography service screening and breast cancer mortality in New Zealand: a National Cohort Study 1999–2011. Br J Cancer. 2017;116:828–39.
3. Oeffinger KC, Fontham ETH, Etzioni R, Herzig A, Michaelson JS, Shih YCT, et al. Breast cancer screening for women at average risk: 2015 Guideline update from the American cancer society. JAMA. 2015;314:1599–614.
4. Heine JJ, Deans SR, Cullers DK, Stauduhar R, Clarke LP. Multiresolution statistical analysis of high-resolution digital mammograms. IEEE Trans Med Imaging. 1997;16:503–15.
5. Mohamed H, Mabrouk MS, Sharawy A. Computer aided detection system for micro calcifications in digital mammograms. Comput Methods Progr Biomed. 2014;116:226–35.
6. Jung NY, Kang BJ, Kim HS, Cha ES, Lee JH, Park CS, et al. Who could benefit the most from using a computer-aided detection system in full-field digital mammography? World J Surg Oncol. 2014;12:168.
7. Qian W, Clarke LP, Song D, Clark RA. Digital mammography: hybrid four-channel wavelet transform for microcalcification segmentation. Acad Radiol. 1998;5:354–64.
8. Tsai NC, Chen HW, Hsu SL. Computer-aided diagnosis for early-stage breast cancer by using wavelet transform. Comput Med Imaging Graph. 2011;35:1–8.
9. Zhang YD, Wang SH, Liu G, Yang J. Computer-aided diagnosis of abnormal breasts in mammogram images by weighted-type fractional Fourier transform. Adv Mech Eng. 2016;8:1–11.
10. Lu W, Li Z, Chu J. A novel computer-aided diagnosis system for breast MRI based on feature selection and ensemble learning. Comput Biol Med. 2017;83:157–65.
11. Warren LM, Mackenzie A, Cooke J, Given-Wilson RM, Wallis MG, Chakraborty DP, et al. Effect of image quality on calcification detection in digital mammography. Med Phys. 2012;39:3202–13.
12. Azavedo E, Zackrisson S, Mejàre I, Heibert Arnlind M. Is single reading with computer-aided detection (CAD) as good as double reading in mammography screening? A systematic review. BMC Med Imaging. 2012;12:22.
13. Pitman AG. Perceptual error and the culture of open disclosure in Australian radiology. Australas Radiol. 2006;50:206–11.
14. Moore W, Ripton-Snyder J, Wu G, Hendler C. Sensitivity and specificity of a CAD solution for lung nodule detection on chest radiograph with CTA correlation. J Digit Imaging. 2011;24:405–10.
15. Suckling J, Parker J, Dance D, Astley S, Hutt I, Boggis C, et al. The mammographic image analysis society digital mammogram database. Exerpta Medica. 1994;1069:375–8.

16. Huang J, Jian F, Wu H, Li H. An improved level set method for vertebra CT image segmentation. Biomed Eng Online. 2013;12:48.
17. Ashwin Kumaar M, Thanaraj P. Feature extraction of Arterio-Venous malformation images using grey level co-occurrence matrix. Indian J Sci Technol. 2015. https://doi.org/10.17485/ijst/2015/v8i35/83387.
18. Wang R, Li C, Wang J, Wei X, Li Y, Zhu Y, et al. Threshold segmentation algorithm for automatic extraction of cerebral vessels from brain magnetic resonance angiography images. J Neurosci Methods. 2015;241:30–6.
19. Xu X, Xu S, Jin L, Song E. Characteristic analysis of Otsu threshold and its applications. Pattern Recognit Lett. 2011;32:956–61.
20. Lai CJ, Shaw CC, Geiser W, Chen L, Arribas E, Stephens T, et al. Comparison of slot scanning digital mammography system with full-field digital mammography system. Med Phys. 2008;35:2339–46.
21. Lewin JM, Hendrick RE, D'Orsi CJ, Isaacs PK, Moss LJ, Karellas A, et al. Comparison of full-field digital mammography with screen-film mammography for cancer detection: results of 4945 paired examinations. Radiology. 2001;218:873–80.
22. Lewin JM, D'Orsi CJ, Hendrick RE, Moss LJ, Isaacs PK, Karellas A, et al. Clinical comparison of full-field digital mammography and screen-film mammography for detection of breast cancer. Am J Roentgenol. 2002;179:671–7.
23. Wallet BC, Solka JL, Priebe CE. A method for detecting microcalcifications in digital mammograms. J Digit Imaging. 1997;10:136–9.
24. Dong M, Lu X, Ma Y, Guo Y, Ma Y, Wang K. An efficient approach for automated mass segmentation and classification in mammograms. J Digit Imaging. 2015;28:613–25.
25. Abdel-Qader I, Abu-Amara F. A computer-aided diagnosis system for breast cancer using independent component analysis and fuzzy classifier. Model Simul Eng. 2008;2008:1.
26. Christoyianni I, Koutras A, Dermatas E, Kokkinakis G. Computer aided diagnosis of breast cancer in digitized mammograms. Comput Med Imaging Graph. 2002;26:309–19.
27. Sahba N, Ahmadian A, Alam NR, Giti M. A hybrid method for mammography mass detection based on wavelet transform. Iran J Med Phys. 2008;5:53–66.
28. Mini MG, Devassia VP, Thomas T. Multiplexed wavelet transform technique for detection of microcalcification in digitized mammograms. J Digit Imaging. 2004;17:285–91.
29. Fenton JJ, Taplin SH, Carney PA, Abraham L, Sickles EA, D'Orsi C, et al. Influence of computer-aided detection on performance of screening mammography. N Engl J Med. 2007;356:1399–409.
30. Huo Z, Giger ML, Vyborny CJ, Metz CE. Breast cancer: effectiveness of computer-aided diagnosis observer study with independent database of mammograms. Radiology. 2002;224:560–8.
31. Tehrani N, Guiti M, Oghabian M, Ahmadian AR, Alam R. Segmentation of suspicious clustered microcalcifications on digital mammograms: using fuzzy logic and wavelet coefficients. Iran J Med Phys. 2003;1:23–8.
32. Niroei M, Abdolmaleki P, Gitee M. Simmulation of a hybrid model using Genetic algorithm and neural network analysis for differentiation of malignant and benign patterns in breast cancer from mammographic findings. Iran J Med Phys. 2007;3:15–22.
33. Sina A, Jalili A, Abdi A, Rafeie R. Study of the mammographic findings and correlation of breast tumors with the pathological results In Imam Khomeini Hospital Urmia. Urmia Med J. 2002;13:213–9.
34. Kim SJ, Moon WK, Cho N, Cha JH, Kim SM, Im JG. Computer-aided detection in full-field digital mammography: sensitivity and reproducibility in serial examinations. Radiology. 2008;246:71–80.
35. Destounis SV, DiNitto P, Logan-Young W, Bonaccio E, Zuley ML, Willison KM. Can computer-aided detection with double reading of screening mammograms help decrease the false-negative rate? Initial experience. Radiology. 2004;232:578–84.
36. Ko JM, Nicholas MJ, Mendel JB, Slanetz PJ. Prospective assessment of computer-aided detection in interpretation of screening mammography. Am J Roentgenol. 2006;187:1483–91.
37. Birdwell RL, Bandodkar P, Ikeda DM. Computer-aided detection with screening mammography in a university hospital setting. Radiology. 2005;236:451–7.
38. van den Biggelaar FJ, Kessels AG, van Engelshoven JM, Flobbe K. Strategies for digital mammography interpretation in a clinical patient population. Int J Cancer. 2009;125:2923–9.
39. Moayedi F, Boustani R, Kazemi AR, Katebi S, Dashti E. Subclass Fuzzy-Svm Classifier As An Efficient Method To Enhance The Mass Detection In Mammograms. Iran J Fuzzy Syst. 2010;7:15–31.